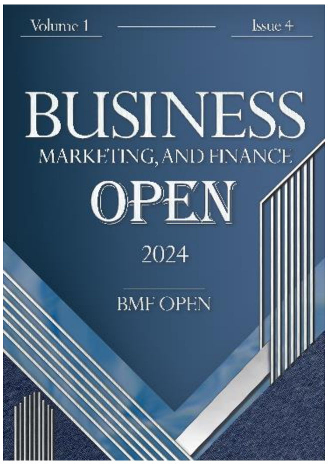
Investigating the Impact of Office Smartization Indicators on the Quality of Financial Processes in Governmental Organizations



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Abstract: This study examines the impact of office smartization indicators on the quality of financial processes in governmental organizations. In terms of purpose, the research is categorized as applied research and, among descriptive methodologies, it is conducted as a case study. The statistical population consisted of employees working in governmental organizations with an unlimited population size, and based on Cochran's formula, a sample of 384 respondents was determined. Following the assessment of variable distribution and descriptive analysis, structural equation modeling was performed using Smart PLS software, and statistical tests were conducted in SPSS. Given that all research hypotheses were confirmed, it can be concluded that office smartization has a significant and positive effect on improving the quality of financial processes in governmental organizations. The utilization of smart technologies, decision support systems, data analytics, and administrative automation enhances accuracy, transparency, speed, and efficiency in performing financial activities. It is recommended that managers, through active engagement with supervisory and regulatory institutions, take steps toward clarifying and updating financial regulations in order to establish a foundation for intelligent decision-making and stable, accountable financial processes.

Keywords: Quality of financial processes, governmental organizations, office smartization.

1. Introduction

The accelerating pace of digital transformation has fundamentally reshaped organizational structures, processes, and governance mechanisms across both private and public sectors. In recent years, artificial intelligence (AI), advanced analytics, robotics, and generative systems have emerged as key drivers of this transformation, redefining how organizations manage resources, design strategies, and deliver services. The integration of AI into managerial and financial domains is no longer a speculative future scenario but a present reality influencing decision-making models, accountability structures, and performance evaluation systems [1, 2]. Particularly within governmental and public sector institutions, the transition toward smart systems and data-driven governance reflects a broader movement toward digital government ecosystems characterized by agility, responsiveness, and technological embeddedness

[3, 4]. These developments signal a paradigmatic shift from traditional bureaucratic administration to intelligent, adaptive, and analytics-oriented public management structures.

Human resource management (HRM) has been one of the core functional areas most profoundly influenced by AI-driven digital transformation. Contemporary HRM is increasingly reliant on data analytics, predictive modeling, and algorithmic decision systems to optimize recruitment, performance management, workforce planning, and competency development [1, 5]. Systematic reviews demonstrate that AI and robotics technologies not only enhance operational efficiency but also transform competency requirements, employee roles, and strategic HR capabilities [2, 6]. Empirical evidence from healthcare and service institutions confirms that AI integration improves HR performance by enabling data-driven insights and reducing procedural inefficiencies [7]. At the same time, the diffusion of intelligent technologies raises concerns regarding job displacement, skill obsolescence, and organizational restructuring, especially in media and communication sectors where automation has already begun to replace routine functions [8, 9]. Thus, the transformation of HRM under AI influence presents a dual dynamic: enhanced strategic capability alongside structural workforce disruption.

Within the financial management domain, AI applications have expanded rapidly, particularly in auditing, financial reporting, compliance monitoring, and risk analysis. Studies demonstrate that the use of AI significantly enhances the quality and reliability of financial statement auditing processes by improving anomaly detection, data processing speed, and predictive accuracy [10, 11]. Similarly, AI-enabled auditing systems align financial reporting objectives with real-time analytical capabilities, thereby strengthening transparency and accountability [12]. The emergence of generative AI in banking and financial services further challenges traditional financial intermediation models, suggesting the potential reconfiguration of institutional roles and service architectures [13, 14]. However, such transformation also introduces regulatory complexity, ethical risks, and governance challenges that require careful policy oversight and compliance frameworks [15, 16].

The public sector has increasingly adopted AI technologies to modernize administrative systems and enhance service quality. Smart government initiatives emphasize the integration of intelligent platforms, digital infrastructures, and data-driven cultures to support strategic decision-making [17, 18]. In turbulent socio-economic contexts, digital government transformation has proven essential for maintaining institutional resilience and operational continuity [3]. Leadership capability and organizational agility are recognized as critical mediators linking digital strategy implementation to performance outcomes [19]. In parallel, meta-synthesis research confirms that AI deployment in public administration improves efficiency, transparency, and citizen-oriented service delivery, provided that institutional readiness and governance frameworks are adequately developed [4]. Nonetheless, the strategic alignment between technological capability and human capital remains a decisive factor in determining the success of digital transformation initiatives.

The interaction between AI, organizational social capital, and future-oriented management practices further underscores the importance of strategic human resource adaptation. Forward-looking HR policies contribute to strengthening organizational trust networks and collaborative capacities, which are essential for sustaining digital transformation trajectories [20]. Forecast-based analyses of AI's role in HR emphasize the necessity of reconfiguring talent management systems to accommodate automation, robotics, and predictive analytics [21, 22]. Moreover, financial markets are experiencing significant AI-driven structural changes, generating both efficiency gains and systemic risks [23]. The adoption of intelligent systems in financial management has been identified as a key driver of innovation, yet it simultaneously requires enhanced regulatory supervision and ethical safeguards to mitigate algorithmic bias and privacy concerns [16, 24]. Consequently, the integration of AI into public financial and human resource systems necessitates a multidimensional analytical framework that considers technological capability, institutional governance, ethical standards, and organizational culture.

From a methodological perspective, multi-criteria decision-making models and advanced evaluation techniques provide structured approaches for assessing the performance and effectiveness of intelligent systems in complex organizational environments [25, 26]. These techniques are particularly relevant in public sector contexts, where multiple stakeholders, regulatory constraints, and accountability mechanisms must be balanced simultaneously. Furthermore, digital transformation research indicates that the quality of financial processes is strongly influenced by technological maturity, human capital competence, and strategic digital alignment [1, 18]. The interplay between AI-enabled auditing, regulatory compliance, and intelligent supervision mechanisms reinforces the necessity of examining how smart systems impact financial process quality in governmental organizations [10, 15]. Despite extensive international research on AI in banking, auditing, and HRM, empirical investigation within governmental financial systems remains comparatively limited, particularly in contexts characterized by evolving regulatory frameworks and digital governance reforms [17, 27]. Therefore, understanding how AI-based smartization influences the quality of financial processes in governmental organizations constitutes a critical research gap with significant theoretical and practical implications.

Accordingly, the present study aims to investigate the impact of artificial intelligence–driven smartization indicators on the quality of financial processes in governmental organizations.

2. Methodology

This study investigates the impact of office smartization indicators on the quality of financial processes in governmental organizations. Accordingly, in terms of purpose, the research is categorized as applied research. With respect to data collection, the study was conducted descriptively using structural equation modeling (SEM) and, among descriptive research designs, is considered a case study. The research is also quantitative in nature.

The statistical population in the quantitative section comprised all employees working in governmental organizations. Due to the large size of the population, a stratified questionnaire was designed based on the qualitative findings of Ferdosipour et al. (2025) to enhance the generalizability of the results. The statistical population was estimated to be unlimited; therefore, using Cochran's formula, a sample size of 384 respondents was determined.

Given that the research was conducted using a survey method, data analysis was performed in two stages: descriptive statistics and inferential statistics. In the descriptive statistics section, statistical indicators, tables, and charts were used to describe the characteristics of the statistical population and the data. In the inferential statistics section, after determining the distribution of variables and conducting descriptive analysis, structural equation modeling (SEM) was performed using Smart PLS software, and statistical tests were conducted in SPSS to examine the relationships among variables and demographic information. The final questionnaire, after expert validation, consisted of two sections:

- Respondents' demographic information, including gender, work experience, education level, and organizational position.
- Questions related to the research variables, designed based on a Likert scale ranging from "strongly agree" to "strongly disagree," aimed at collecting data regarding the components and dimensions of the variables.

3. Findings and Results

Based on the descriptive statistics results, the highest frequency among respondents by gender was male, with 233 individuals (60.7%), while females accounted for 39.3% of the participants. The largest group of respondents was between 35 and 45 years of age, with a frequency of 179 individuals, whereas the smallest group was between 25 and 35 years, with a frequency of 51 individuals. Regarding educational level, the majority of respondents held a doctoral degree or higher (238 individuals), while the smallest group held a bachelor's degree (37 individuals). In terms of work experience, the results indicate that most respondents had between 10 and 15 years of experience in governmental organizations, representing 62% of the total respondents.

According to the information presented in Table 2, comparison of the standard deviations of the variables under study indicates that the political and legal factors variable exhibits the highest dispersion, whereas the social and innovation factors variable shows the lowest dispersion. In general, a lower standard deviation among components indicates lower variability in responses. Furthermore, the mean value of each variable reflects its overall level. Among the variables, social and innovation factors demonstrate the highest mean, indicating a higher average response range, while political and legal factors have the lowest mean, reflecting more concentrated responses in this area. Additionally, skewness and kurtosis values indicate that skewness for all variables falls within the range of (−2 to +2), whereas kurtosis values for all components do not fall within this range. Therefore, it can be concluded that the data distribution for all components is non-normal. For further verification, the Kolmogorov–Smirnov test was employed, the results of which are presented below.

Table 1. Inferential Statistics of Research Variables

Statistic	Social and Innovation Factors	Office Smartization	Political and Legal Factors	Intelligent Decision-Making	Quality of Financial Processes
Sample Size (Valid)	384	384	384	384	384
Missing	0	0	0	0	0
Mean	4.163	4.020	3.476	3.933	4.062
Standard Deviation	1.0122	1.0236	1.2494	1.0468	1.0303
Skewness	−1.960	−1.652	−0.525	−1.450	−1.750
Kurtosis	3.503	2.297	−0.902	1.640	2.626
Minimum	1.0	1.0	1.0	1.0	1.0
Maximum	5.0	5.0	5.0	5.0	5.0

To assess the measurement models, three criteria were employed: indicator reliability, convergent validity, and discriminant validity. Indicator reliability was evaluated using three measures: (1) Cronbach's alpha, (2) composite reliability, and (3) factor loadings.

Table 2. Model Assessment Based on Measurement Criteria

Variable	Composite Reliability	AVE	Cronbach's Alpha
Intelligent Decision-Making	0.960	0.707	0.953
Social and Innovation Factors	0.952	0.798	0.936
Political and Legal Factors	0.933	0.737	0.911
Office Smartization	0.936	0.746	0.913
Quality of Financial Processes	0.969	0.756	0.964

According to this criterion, the values located on the main diagonal of the matrix, which represent the square roots of AVE obtained in previous stages, must be greater than the corresponding off-diagonal values in the same column. Based on the results presented in Table 2, this condition is satisfied. Therefore, it can be concluded that discriminant validity is established in the model and that discriminant validity in the structural model is at an acceptable level.

Table 3. Discriminant Validity

Variable	Intelligent Decision-Making	Social and Innovation Factors	Political and Legal Factors	Office Smartization	Quality of Financial Processes
Intelligent Decision-Making	0.841				
Social and Innovation Factors	0.908	0.893			
Political and Legal Factors	0.772	0.696	0.859		
Office Smartization	0.911	0.924	0.726	0.864	
Quality of Financial Processes	0.953	0.953	0.748	0.932	0.869

Factor loadings or path coefficients indicate the magnitude and percentage of the effect of independent variables on dependent variables; however, they do not constitute the basis for hypothesis acceptance or rejection. As shown in Figure 1, the factor loading values for all relationships exceed 0.20, which is considered acceptable. The only relationship with a relatively low value is between empowering leadership and creativity, with a coefficient of 0.150; nevertheless, hypothesis acceptance or rejection is determined based on the t-statistic. As illustrated in Figure 2, the t-statistic values for all relationships exceed 1.96, indicating the acceptance of the corresponding hypotheses at the 95% confidence level.

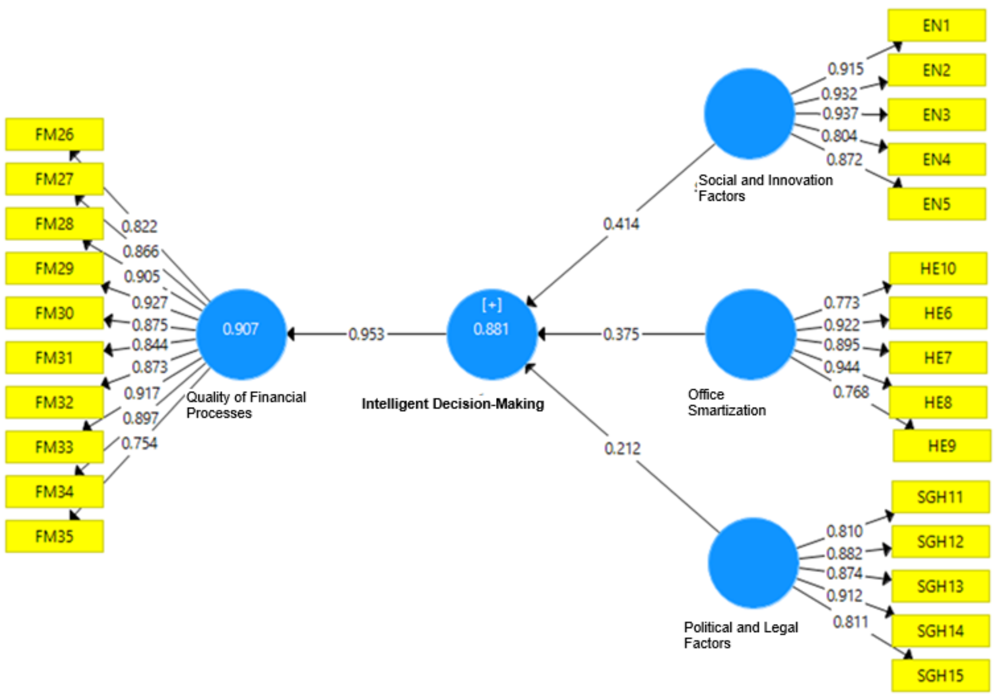

Figure 1: Factor Loadings in the Research Model

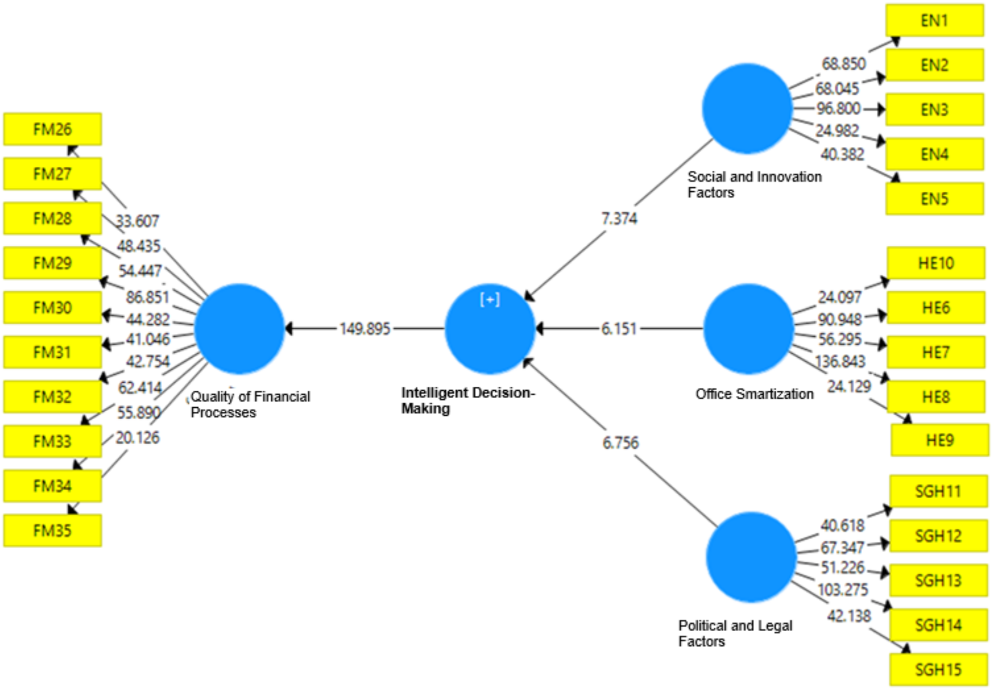

Figure 2: T-Statistic Values in the Research Model

In this study, the threshold value of 0.30 was considered for the evaluation indices R^2, f^2, and redundancy. As presented in Table 4, the exogenous variables in this study exhibit values greater than 0.30, indicating good to excellent structural model fit.

Table 4. R^2 Values in Structural Model Fit

Variable	R Square	f^2 Values	Redundancy	Q^2 Value
Intelligent Decision-Making	0.881	0.881	0.444	0.617
Quality of Financial Processes	0.907	0.907	0.416	0.681

The Communality values obtained from the software output were averaged and then multiplied by the square root of R^2. The result of this multiplication yields the Goodness-of-Fit (GOF) index, the results of which are presented in Table 5. In this study, the GOF value was calculated as 0.863, indicating a very strong model fit.

Table 5. GOF Index Value

Variable	Communality
Intelligent Decision-Making	0.621
Social and Innovation Factors	0.863
Political and Legal Factors	0.797
Office Smartization	0.696
Quality of Financial Processes	0.865
Mean	0.779
R^2	0.915
GOF	0.863

The Standardized Root Mean Square Residual (SRMR) is one of the goodness-of-fit indices in structural equation modeling, representing the average discrepancy between the observed correlation matrix and the model-implied correlation matrix. Its value ranges between 0 and 1, and values less than 0.08 (or, in some references, less than 0.05) indicate good model fit. As shown in Table 6, the results demonstrate a strong model fit.

Table 6. SRMR Index

	Saturated Model	Estimated Model
SRMR	0.070	0.074
d_ULS	3.088	3.434

The Sobel test is used to examine the significance of mediating effects in regression or structural equation models. In this test, the path coefficients between the independent variable → mediator variable and the mediator variable → dependent variable are evaluated to determine whether the indirect effect of the independent variable on the dependent variable through the mediator is statistically significant. If the Sobel test statistic is greater than 1.96 or less than −1.96 (at the 95% confidence level), the mediating effect is considered significant. As reported in Table 6, this analysis confirms the mediation effects, and all relationships in the model are supported. Based on the data analysis results presented above, all hypotheses of the model were confirmed.

Table 7. Sobel Test Results

Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics	P Values
Social and Innovation Factors → Quality of Financial Processes	0.395	0.394	0.054	7.299	0.000
Political and Legal Factors → Quality of Financial Processes	0.202	0.204	0.030	6.793	0.000
Office Smartization → Quality of Financial Processes	0.357	0.356	0.058	6.178	0.000

4. Discussion and Conclusion

The findings of this study demonstrate that artificial intelligence–driven smartization indicators exert a significant and positive effect on the quality of financial processes in governmental organizations. The structural model results confirmed that social and innovation factors, political and legal factors, and office smartization directly and indirectly enhance financial process quality, with intelligent decision-making playing a central mediating role. The high R^2 values obtained for intelligent decision-making and financial process quality indicate that the explanatory power of the model is substantial, suggesting that the integration of AI technologies into public administrative systems meaningfully contributes to improved transparency, efficiency, and accountability. These results align with contemporary digital transformation research emphasizing that AI-enabled systems enhance operational effectiveness and strategic agility within public institutions [1, 3].

One of the most important findings concerns the strong relationship between office smartization and intelligent decision-making. The results suggest that when governmental organizations adopt AI-based tools, data analytics platforms, and automated workflows, they significantly improve their capacity to make evidence-based financial decisions. This outcome is consistent with research indicating that digital transformation strengthens data-driven cultures and enhances intelligent decision-making capabilities in public organizations [18]. Similarly, leadership agility and digital strategy alignment have been identified as key enablers of effective digital transformation outcomes, reinforcing the mediating role of intelligent decision systems observed in this study [19]. The empirical confirmation of intelligent decision-making as a mediator also supports arguments that AI does not merely automate processes but reshapes managerial cognition and analytical depth within financial governance frameworks [13, 14].

The significant effect of social and innovation factors on financial process quality highlights the importance of organizational readiness and innovation culture in successfully implementing AI technologies. Organizations characterized by openness to innovation, knowledge sharing, and adaptive learning are more capable of leveraging AI to improve financial accuracy and responsiveness. This finding is consistent with systematic reviews showing that digital transformation effectiveness depends heavily on employee competencies and innovation-oriented cultures [2, 6]. Furthermore, empirical studies confirm that AI integration enhances human resource performance and operational outcomes when organizational capabilities support technological adoption [7]. The current findings therefore reinforce the argument that technological investment alone is insufficient; rather, social capital and collaborative networks within organizations significantly influence the quality of digital financial processes [20].

The results also confirm that political and legal factors significantly influence financial process quality. Regulatory clarity, compliance mechanisms, and institutional oversight frameworks appear to play a crucial role in ensuring that AI-driven systems enhance rather than undermine financial governance. This observation aligns with research highlighting the regulatory implications of AI deployment in financial institutions [15]. Ethical concerns, data privacy issues, and accountability risks associated with algorithmic systems have been widely discussed in the literature [16, 24]. In the context of auditing and financial reporting, AI applications can improve precision and fraud detection, yet they must operate within robust legal frameworks to maintain public trust [10-12]. The significant path coefficient observed for political and legal factors suggests that institutional governance structures moderate the effectiveness of AI-based financial processes, confirming the necessity of regulatory alignment in digital government initiatives [17].

Moreover, the findings reveal that AI-driven smartization substantially improves the overall quality of financial processes, including speed, transparency, reliability, and accuracy. This result corresponds with studies documenting AI's transformative impact on financial management and auditing systems [23, 27]. In banking and financial services, generative AI and advanced analytics have been shown to reduce operational risk and enhance compliance monitoring, indicating similar mechanisms may operate in public financial systems [13, 14]. The integration of AI technologies into HR and administrative systems further strengthens financial governance by enabling predictive workforce planning and optimized resource allocation [5, 21, 22]. These findings collectively suggest that AI functions as an integrative enabler linking human capital development, digital infrastructure, and financial accountability within governmental organizations.

The mediating role of intelligent decision-making also reinforces the notion that AI-driven transformation must be strategically embedded rather than technically isolated. Studies indicate that AI's impact on HR and organizational performance is contingent upon structured implementation and decision-support integration [28]. Additionally, automation may result in job restructuring or displacement if strategic workforce planning is neglected [8, 9]. The present study's findings imply that governmental organizations can mitigate such risks by leveraging AI to augment rather than replace managerial expertise, thereby fostering collaborative human–machine decision architectures. Multi-criteria decision-making approaches further support structured evaluation of AI-enabled governance systems and enhance strategic alignment in complex institutional environments [25, 26].

In summary, the results confirm that AI-based smartization significantly enhances financial process quality in governmental organizations through the combined effects of technological capability, innovation culture, regulatory alignment, and intelligent decision-making. The findings contribute to the growing body of literature emphasizing that AI integration in public financial systems requires a balanced approach encompassing strategic leadership, ethical safeguards, and institutional readiness [1, 4].

The study has several limitations. First, the data were collected from governmental employees within a specific administrative context, which may limit the generalizability of the findings to other sectors or countries with different institutional frameworks. Second, the cross-sectional research design restricts the ability to draw causal inferences or examine long-term impacts of AI-based smartization. Third, reliance on self-reported questionnaire data may introduce response bias or subjective evaluation effects. Finally, while the structural model demonstrated strong explanatory power, qualitative dimensions such as organizational resistance, ethical perception, and managerial cognition were not directly explored.

Future research should adopt longitudinal designs to assess the long-term sustainability and dynamic evolution of AI-driven financial systems in governmental organizations. Comparative studies across countries or between public and private sectors could provide deeper insight into contextual differences in digital transformation effectiveness. Additionally, mixed-method approaches incorporating qualitative interviews or case studies would enrich understanding of managerial perceptions and cultural adaptation processes. Further research may also examine moderating variables such as leadership style, organizational size, digital maturity level, and regulatory environment to refine theoretical models of AI integration in public financial governance.

From a practical perspective, policymakers and public managers should prioritize strategic digital planning that integrates AI technologies with institutional governance reforms. Investments in employee training and digital competency development are essential to ensure that intelligent systems are effectively utilized. Regulatory bodies should establish transparent frameworks for AI governance, emphasizing data protection, ethical standards, and accountability mechanisms. Finally, fostering an innovation-oriented organizational culture that encourages experimentation and cross-functional collaboration will strengthen the positive impact of smartization on financial process quality.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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